Mapping street lighting: Illuminance characterization in urban squares in the Brussels Capital Region

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Abstract. Recent literature has acknowledged the critical role street lighting plays in the urban environment, influencing economic growth, human health, biodiversity, pedestrian safety, light pollution, and mobility, amongst others. Street lighting has also become a subject of ongoing discourse due to its energy use and the associated environmental impacts. Balancing the benefits of urban street lighting for environmental wellbeing, while considering energy use, requires identifying appropriate lighting conditions for pedestrians to inform urban policies and implementations, as well as the necessary data to accurately support such decisions. However, most cities fail to document current street lighting conditions through methods such as geospatial, or nighttime aerial imagery analysis, leaving lighting conditions unknown for most municipalities and thereby limiting the potential for their effective amendment, implementation, or assessment. This paper presents the AI LUX tool, which is based on a novel methodology combining street level 360° images, and machine learning computer visions algorithms, to document street level illuminance. The paper also explains the findings of a field campaign conducted in 10 urban squares located in the Brussels Capital Region, where, using illuminance sensors, a geospatial mapping of the street illuminance conditions was performed. This data was then used to calibrate and validate the AI LUX tool. The results show a robust agreement between the field measurements and the illuminance ratio obtained from the AI LUX tool. Given the increasing availability of Google Street View (GSV) and 360º nighttime imagery, the AI LUX tool proposes a scalable workflow to efficiently compute street illuminance.

1. Introduction.

Street lighting represents a key component of Urban Lighting Infrastructure (ULI), one of the main foundations of the constantly growing contemporary urban model [1]. From the use of oil lamps in the ancient greek and roman times to illuminate paths, to the emergence of LED technology and smart lighting systems, urban illumination has continuously evolved to enhance nighttime use [2]. The implementation of street lighting has been guided by the idea of more illumination provide more safety, responsible of issues such as light pollution and energy consumption. The importance of street lighting in the urban ecosystem has been acknowledged for its impact on: i) economic development, as a factor related to the growth of human activities and wealth, particularly in highly developed regions [3], ii) light pollution, gauging the effects on increased night sky brightness, and its consequences to ecosystems as a recognized disruptor of biological functions and animal life [4], iii) energy, considering the impact on economy and environmental sustainability [5], iv) mobility, to promote better visibility and, subsequently, reduce the risks of traffic accidents [6], v) safety, to prevent crime and promote the use of public spaces [7], and vi) human health, considering the impacts on vision and the risks of effects on sleep disruption and mental disorders [8]. Since street lighting implies a wide range of impacts, the definition of a balance between light pollution, safety and energy demands is among the most prevalent challenges that city stakeholders need to urgently tackle [9].

Recent literature on street lighting has explored various lighting configurations aimed at promoting energy efficiency and reducing environmental impact, while ensuring street safety [10]. From a data compilation point of view, some of these studies have made use of street-level data collection practices, using field measurements [11], lighting technical documentation [12], and field observations experiments [13]; through hand-held devices which have shown to constrain the study area. Other studies have analyzed street lighting at the meso scale, using remote sensing [14] or georeferenced data [15]; allowing for larger-scale studies, with the disadvantage that the spatio-temporal resolution limits studies focusing on the pedestrian perspective. One study that explored the relationship between public perception and lighting attributes combined satellite imagery (Beijing's SDGSAT-1) with ground-measurements (CL-500A spectrophotometer), revealing the necessity to enrich large-scale datasets with local data, to perform pedestrian level studies [16]. From a methodological perspective, some studies have also explored machine learning approaches for predicting outdoor illumination using images [17], 3D point clouds [18], and georeferenced point data [19]. Other studies have explored similar methods to foresee lighting in indoor and/or virtual scenarios [20]. For example, a recent study proposed a model -trained by low dynamic range (LDR) and high dynamic range (HDR) images- to predict indoor illumination from a 360° image [21]. However, to the best of our knowledge, no scientific studies have presented a machine learning method for predicting street lighting illuminance using 360° nighttime images captured at the pedestrian level.

This paper presents the AI LUX tool, which is based on a novel methodology combining street level 360° images, and machine learning (ML) computer visions algorithms, to document street level illuminance. The paper also presents the findings of an experimental campaign conducted in 10 urban squares located in the Brussels Capital Region (BCR), where, using illuminance sensors, a geospatial mapping of the street illuminance conditions was performed. This data was then used to calibrate and validate the tool. Given the increasing availability of Google Street View (GSV) and 360º night-time imagery, the AI LUX tool proposes a scalable workflow to efficiently compute street illuminance.

2. Methodology

2.1. Field campaign

To train and validate the AI LUX tool, 360° nighttime images and illuminance measurements were collected. An experimental campaign was organized focusing in 10 urban squares located in two of the densest municipalities of the BCR -St. Gilles and Molenbeek-.

2.1.1. Criteria. In order to define the data collection conditions aiming for stable illuminance conditions, working nights, between July and August 2022 were selected. The night selection criteria included: i) nights with a maximum lunar illumination of 25%,; ii) the hours of data collection were set up between night and astronomical twilight to reduce the spectral irradiance of the sky; and iii) a grid-based data collection method for the illuminance measurements, and orthogonal mesh whose dimension are in relation to the urban dimension (<1000 m^2 = 5x5 m, 1000-4999 m^2 = 10x10 m, 5000-9999 m^2 = 15x15 m, 10000-49000 m^2 = 20x20 m, >50000 m^2 = 25x25 m).

2.1.2. Data type. For each point in the grids, and for all urban squares studied: i) georeferenced coordinates were obtained using a Topcon FR-500 geodesic station equipped with a HiPer VR GNSS receiver in a real-time kinematic (RTK) mode. This setup provides real-time positioning with an accuracy of ± 8mm allowing precise identification of the points; ii) horizontal illuminance was measured with a Eurotest 61557 MI 2086 multifunctional lighting instrument, compliant with the IEC/EN 61557 international standard for electrical testing equipment. The device was equipped with a lux meter with a measurement range of 0.1 lux to 20 kLux and a precision of ± 0.01 lux; and iii) 360° standard dynamic range (SDR) night-time photographs were captured using a Go-Pro Hero camera. SDR photographs were selected over HDR photographs for several reasons, including the fact that they can yield reliable and repeatable light measurements, as noted in earlier research [22,23]. Firstly, SDR images ensures more scalability, as they can be taken with smartphones or downloaded from GSV imagery. Secondly, even though HDR photos can depict a wider range of brightness by combining multiple exposures, their accuracy in measuring illuminance may be limited in dynamic urban scenes due to changing lighting conditions and movement which can cause blurriness and artefacts. Lastly, minimizing image size and computational processing was aimed for its functionality in mobile application.

2.2. AI LUX tool

This paper presents a novel tool for mapping illuminance and characterizing night-time outdoor lighting scenarios at the pedestrian level informed by lighting regulations. It adheres to EN 13201-2 [24] for pedestrian and cyclist areas (2-15 lux) and Brussels Environment recommendations [25] for green spaces (max 25 lux, ideally 10 lux). Therefore, the model considers well-lit for non-green areas as P1 (3-15 lux) and green areas as P2 (2-10 lux). The use of the tool is illustrated (Figure 1).

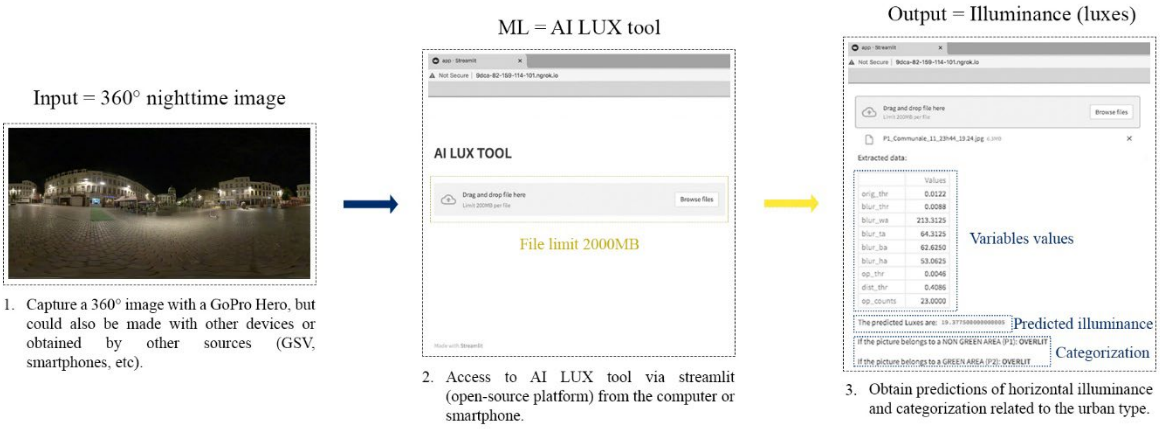

Figure 1. AI LUX tool operation**.**

For the development of the AI LUX tool based on ML model, the Python programming language has been used, along with open-source libraries such as: OpenCV (focused on artificial vision), Pillow (support for image file manipulation), Pandas (for data handling), NumPy (for numerical computations), Pickle (for model serialization), and Scikit-learn (for the ensemble module). Additionally, Streamlit was used to allow for an interactive visualization of the tool via internet. To define the most suitable prediction approach, different ML methods (classification and regression) and techniques (bagging, random forests, and boosting) were evaluated. From these, the AdaBoost.RT model [26] was chosen due to its superior predictive performance. The AdaBoost ensemble regression model uses 50 DecisionTreeRegressor estimators (depth maximum = 3) and a learning rate of 1.0, balancing complexity and predictive performance. The model used 513 images distributed across different illuminance ranges: <2 lux (63), 2-3 lux (37), 3-10 lux (140), 10-15 lux (89), and >15 lux (184). This dataset was split following 70 - 30% ratio, ensuring proportional representation of illuminance levels for training and validation.

Due to the limited data sample, data augmentation techniques were employed to enhance the training procedure. The traditional techniques such as cropping or adjusting brightness were not applicable, so artificial salt-and pepper noise was introduced to modify pixel values while maintaining the overall ratio. Therefore, the model utilized ten parameters categorized in two groups: i) image processing techniques, that enhance key structures in the image and refine the prediction process: thresholding (thr_orig), gaussian blur littering (blur), morphological transformations (op), and distance transform filtering (dist); and ii) image characterization metrics, that quantify spatial characteristics and provide insight into the lighting distribution: threshold ratios (thr), segmentation cluster count (count), width angle coverage (wa), height angle coverage (ha), bottom angle coverage (ba), and top angle coverage (ta) [27]. The importance of each variable was assessed using Mean Decrease in Impurity (MDI), which quantifies the reduction in variance when a feature is used for decision splitting [28], and the linear relation between variables was addressed using the Pearson correlation coefficient through a correlation matrix including the features for the model prediction (Figure 2).

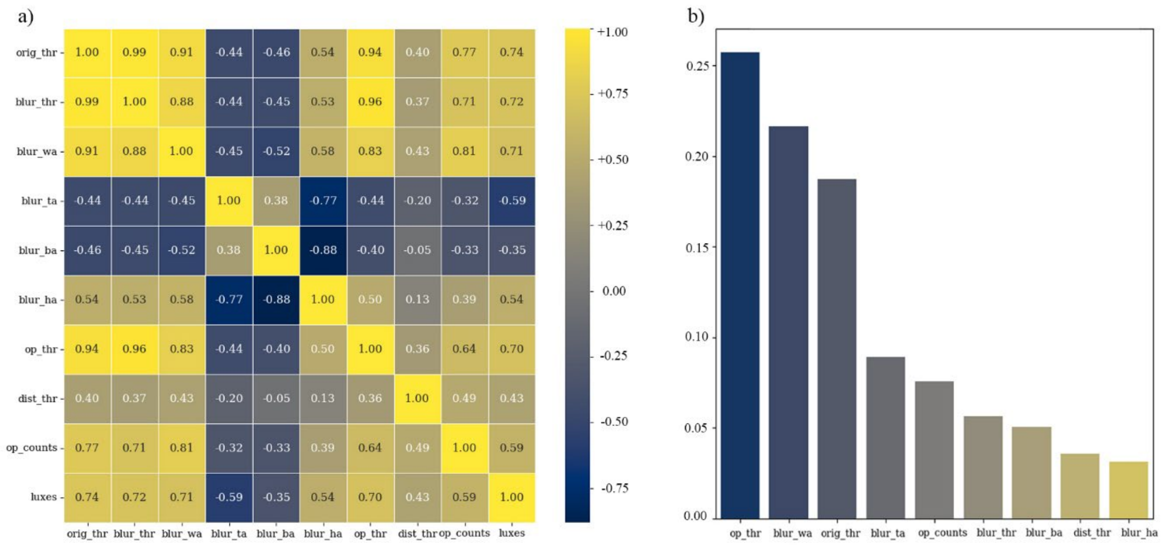

Figure 2. The prediction model variables. (a) Pearson correlation matrix, (b) MDI distribution.

2.3. Validation and calibration method

To ensure the reproducibility of these results in different conditions, a photometric calibration was conducted to guarantee maximum correlation for lux measurements in nocturnal environments. This process involved two main steps: i) radiometric calibration to ensure that the pixel values of the 360° images could be correlated with the photometric units of illuminance, and ii) exposure correction based on adjustments to ISO and shutter speed to prevent images from being too dark or overexposed.

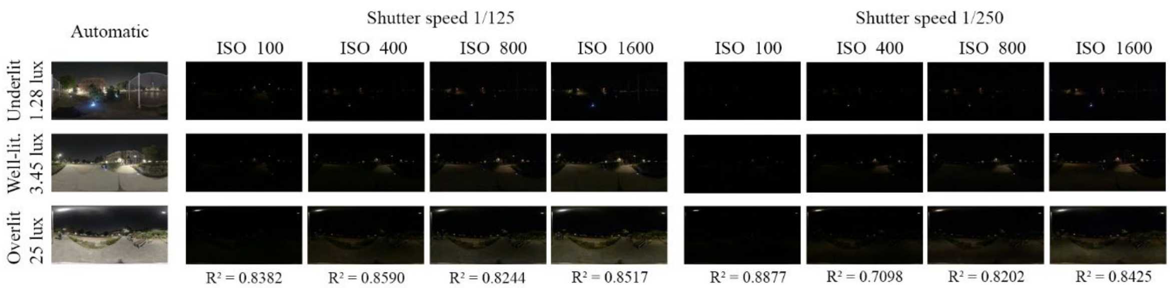

Figure 3. Photometric calibration

A total of 40 shots were taken at different points, covering a lighting range from 1 to 23 lux, to represent various scenarios (underlit, well-lit, and overlit). Each shot was taken with a combination of different

ISO settings (100, 400, 800, 1600) and shutter speeds (1/125 and 1/250). A regression analysis was performed, including error metrics such as MSE, RMSE, and MAE. Finally, the ISO 1600 and shutter speed of 1/125 setup was chosen, as it exhibited the best correlation while maintaining a stable relationship between high and low lighting zones in the image (Figure 3). This setup proved to be particularly effective in low-light areas, where lower ISOs would not produce adequate results. In addition, ML parameters, including thresholding, blur, morphological operations, aperture adjustments, and distance filters, were applied to enhance image quality and optimize lux computations.

3. Results

The horizontal illuminance data across 513 different points in 10 urban squares revealed that 43.66% were overlit, 41.52% were well-lit and 14.82% were underlit, according to the lighting normative. Also, notable variability was observed among the different squares, with some areas exhibiting significantly higher illuminance levels (Place Comunale) than others (Place Morichar) (Figure 4).

3.1 Validation results

The performance of the AI LUX tool was evaluated though the study of error metrics such as MAE= 4.51 lux and RMSE=6.09 lux, indicating an average deviation of ±4.51 lux and a standard deviation of ±6.09 lux in the lighting predictions. The model explains 78% of the variance of the collected lux measurements, showing an acceptable predictive power. A comparison of the collected and predicted illuminance for each square is shown (Figure 4). In the same figure, dashed lines representing the -underlit, well-lit and overlit- bounds for each type (P1 and P2) as per lighting code are also included.

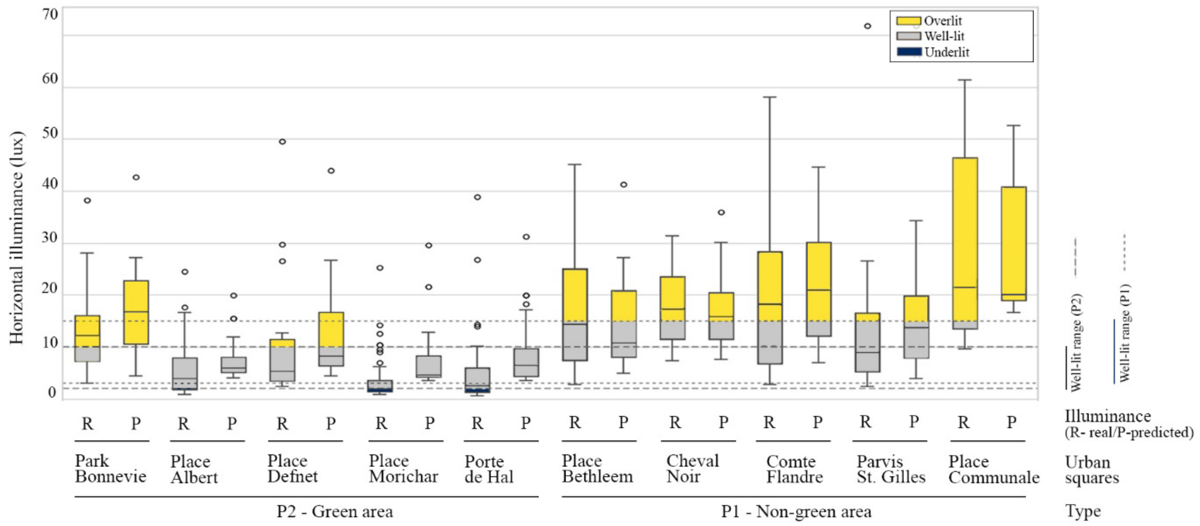

Figure 4. Horizontal illuminance distribution for each urban square by illuminance category.

The lighting measurements and predictions were also spatially represented using interpolation algorithms such as Inverse Distance Weighting (IDW) in QGIS to visually evaluate the differences between the measured and predicted lux and hence assess the performance of the AI LUX tool for one urban square (Figure 5). The maps show the points classified as well-lit in white, and those overlit in yellow. Qualitatively we can observe a robust agreement between the field measurements and the illuminance ratio obtained from the AI LUX tool. The most challenging areas for the AI LUX tool remain those underlit points in blue in the measurements map, with an error of ±4.51 lux in the predicted lux. Due to this error, those points are tagged as correctly illuminated -shown in white- in the prediction map. This change is also affected by the small range of the underlit category (P1: 0–3 lux, and P2: 0–2 lux), which is smaller than the error.

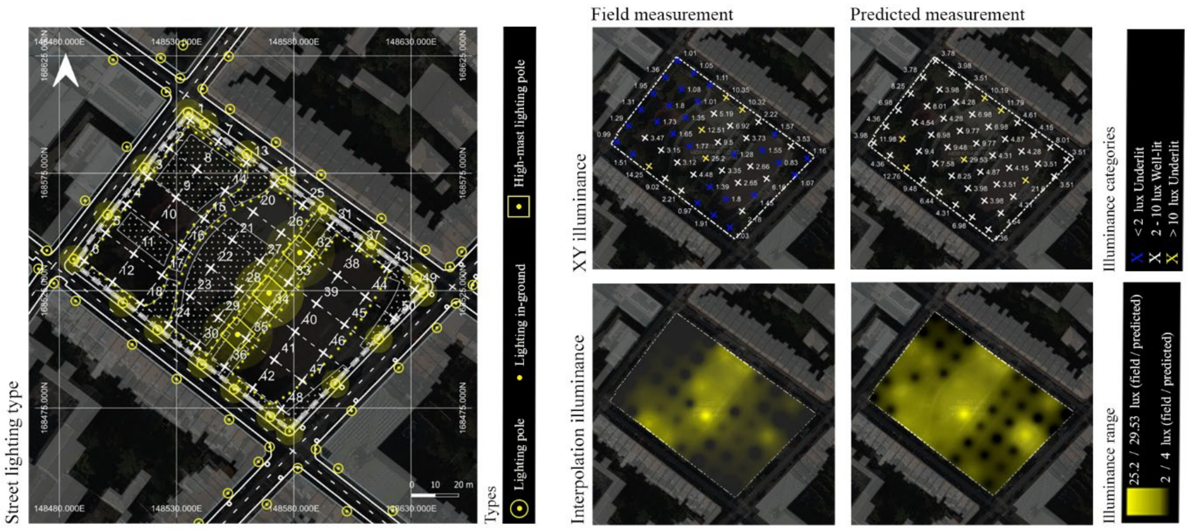

Figure 5. Horizontal illuminance distribution map.

3.2 Limitations and next steps

The AI Lux tool proved a reliable model to predict illuminance using 360° images, however the limitations of the tool are to be considered for future development and use. The first limitation is its challenge to forecast underlit pictures. Further studies are necessary to assess whether this was due to the training data used, which included a low ratio of underlit images (20%) compared to other categories. The second limitation is related to the inaccuracies that can be brought along given changes in weather conditions. Hence, considering weather conditions and potentially integrating autocorrection parameters based on them can be beneficial, allowing the model to adjust for images collected under varying meteorological conditions, such as clear skies or rain. The third limitation is related to the urban environment, which, in the night-time images collected, may not be representative of real-time conditions, considering changes in greenery, commercial lighting, and other factors. Following this initial study, further steps will be taken, which will include gathering a bigger sample of training data to enhance the tool's performance.

4. Conclusions

This paper presents the AI LUX tool, which is based on a novel methodology combining street level 360° images, and ML computer visions algorithms, to document street level illuminance at nighttime. The results comparing 10 urban squares located in BCR have been presented. The horizontal illuminance measurements revealed that 43.66% were overlit, 41.52% were well-lit and 14.82% were underlit, with a notable variability among the different squares. The illuminance measurement and prediction data were analyzed statically to evaluate the model's performance, giving an average deviation of ±4.51 lux and a standard deviation of ±6.09 lux in the lighting predictions. The model explains 78% of the variance of the collected lux measurements, showing an acceptable predictive power. These data were also spatially represented, showing qualitatively a robust agreement between the field measurements and the illuminance ratio, and remaining the underlit areas the most challenging to predict. Following this preliminary study, a larger sample will be collected and autocorrection parameters studied to improve the tool performance. Overall, the AI LUX tool is effective to compute street lighting illuminance.

Acknowledgements

Research financed by Innoviris – Applied PhD Innoviris 2023 Grant (RBC / 2023 – PHD- 11).

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